Multimodal Registration Using Stereo Imaging and Contact Sensing

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***Abstract*—Registration plays an important role in robot assisted minimally invasive surgeries, by localizing the tool-tip onto the preoperative model of the anatomy. Contact-based point measurements have been typically used to perform registration. However, a lot of time is spent in moving the robot tool to obtain these measurements. On the other hand, stereo imaging quickly provides thousands of point measurements, but these measurements are affected by noise in the measurements as well as artifacts such as occlusions and specular reflections. In this work, we use both stereo and contact measurements in a complementary manner to obtain fast and accurate registration estimates. We show that stereo measurements provide fast and approximate registration estimates, which can then be refined with as few as 10 contact measurements. We validate our approach with experiments performed using a daVinci surgical robot on femur bone and silicone phantom tissue. In comparison with the popular registration method iterative closest point, our approach is faster by an order of magnitude.**

I. Introduction

Robot assisted minimally invasive surgery (RMIS) has potential benefits over open surgery such as reduced trauma, improved dexterity, reduced risk of infection and postoperative hospital stay [12]. However, unlike in an open surgery, where the physician can visually and tactually understand the operating site, there is a lack of direct sensory presence in RMIS. Hence the physician needs to make a correspondence between the location on the preoperative model and the current location of the robots tool-tip. This process is called registration and it is a vital first step for directing the robot to important regions of interest. Our work advances the state-of the-art in registration; it fuses complementary information– stereo imaging and point contact measurements, to perform robust and accurate registration.

Stereo imaging provides thousands of point measurements, but the measurements are often noisy and affected by occlusions and specular reflections [3, 10]. Contact sensing, on the other hand, provides more accurate point measurements that are not affected by the above factors [18, 19]. However, there is a cost associated with moving the robot-tool to obtain each contact measurement; and hence only a small number of sparse contact measurements are often available [8]. In this work, we first use stereo measurements to estimate a quick and approximate registration estimate using a filtering-based approach [21]. Contact sensing is then used to improve the registration estimate. A probabilistic sparse registration method is used to process the contact measurements and obtain an accurate registration estimate [20]. The estimated registration is finally used to overlay the preoperative model on the intraoperative visuals to aid the surgeon during a procedure.

In order to validate our approach, we register a daVinci surgical arm to preoperative models of a femur bone and a silicon soft tissue. On comparison with iterative closest point (ICP) [2], our approach is accurate and requires lesser computation time. The registered pose of the preoperative models also visually conforms well to the intraoperative images.

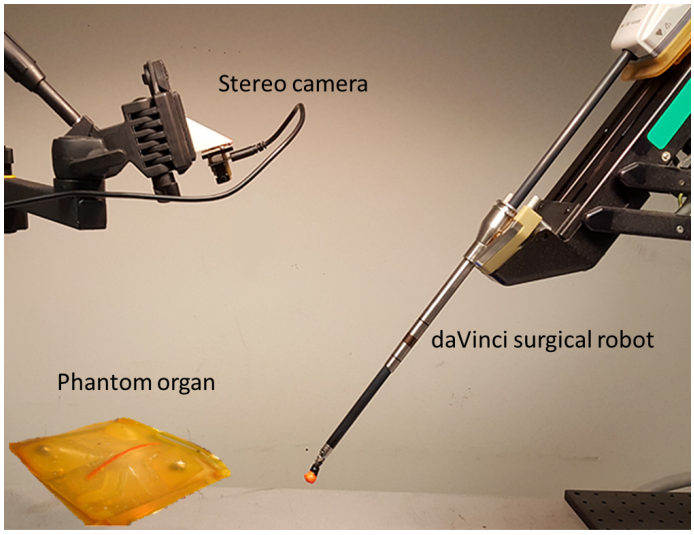

Fig. 1. Experimental setup showing stereo camera, daVinci surgical robot and the phantom organ.

II. Background

Registration is frequently encountered in robotic applications, such as computer vision [7], localization and mapping [11], surgical guidance [8], etc. Besl et al. came up with the popular iterative closest point (ICP) method that recursively finds correspondences and minimizes the alignment difference between point sets [2]. Over the years several variants of the ICP have been developed [16], and also filtering-based solutions have been developed that are better at handling noise in the data and provide online estimates [9].

Prior work on stereo registration for surgical applications achieve accuracies of $\approx 2-3$mm and take several seconds of computation time [4]. Recently a filtering-based approach was developed by our group, that uses a linear update model and produces robust, fast and accurate pose estimates compared to prior methods [21]. We use this approach for performing the stereo registration in this work.

Probing-based registration methods are more accurate than stereo registration, with RMS errors less than 0.5mm [8]. However, they require more than 100 contact measurements, which can take several minutes to be obtained [19]. In our prior work, we developed an approach that probabilistically estimates the registration using 20-25 contact point measurements [20]. In this work, we use this approach for estimating registration using contact measurements.

III. Modeling

Two objects of anatomical interest were used to test our approach: a 3D printed model of femur bone and a silicon phantom organ. The bone presents a feature rich surface for stereo reconstruction whereas the silicon phantom has fewer visual features and provides for a more challenging scenario to test our approach.

The experimental setup consists of a daVinci surgical robot, an ELP stereo camera (model 1MP2CAM001) overlooking the workspace of the robot and contact sensing by monitoring the current at the joints of the robot (See fig. 1). The current sensing at the joints of the robot can be calibrated to estimate contact force magnitude. We consider the robot to have contacted the organ if the sensed force is greater than an empirically found threshold (We use a threshold of $10g$ force in this work).

The procedure is as follows:

1) The intrinsic and extrinsic parameters of the stereo camera are calculated using standard calibration routines [13]. Hand-eye calibration is also performed to find the relative pose between the camera and the robot. The position of the tip of the robot-tip is obtained from the camera images as well as from the robot kinematics. The relative pose between these position measurements is computed using Horn's method [5].
2) The user manually crops the region of interest by defining a bounding box and the points belonging to the organ are segmented using GrabCut [14], as shown in Fig. 2(b). A point cloud of the visual environment is reconstructed and visualized using the daVinci stereo viewer [7] (See Fig. 2(c)).
3) An interactive preoperative model of the organ is then placed virtually in the field of view by user. Fig. 2(d) shows the preoperative model in blue.
4) A Bingham filter-based pose estimation approach [21] is used to register the point cloud obtained in Step 2 to the preoperative model in Step 3. This provides an approximate transformation for aligning the object with the available stereo view, as shown in Fig. 2(e).
5) A user tele-manipulates the robot and makes contact with the organs surface at arbitrary locations. The contact points are recorded and used for registration with the estimated pose of the preoperative model obtained in Step 4. A sparse point registration [20] is used to register the object to the model. This step improves the registration further (see Fig. 2(f)), and converges to the true location of the organ with as few as 10 points.

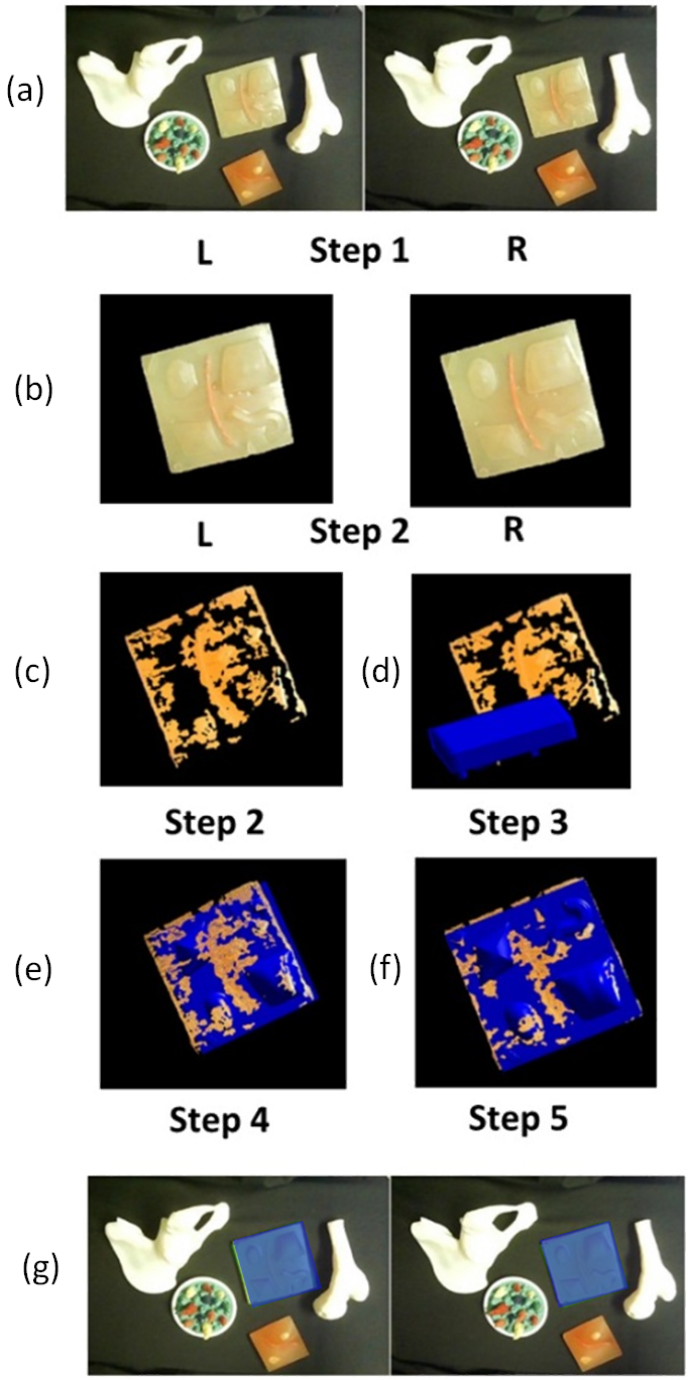

Fig. 2. Steps taken for registration of preoperative model to stereo view. (a) Left and right camera views. The object of interest is the silicone phantom in the centre. (b) The silicone phantom is segmented in the left and right camera images. (c) 3D reconstructed surface of the silicone phantom. (d) The preoperative model of the phantom, shown in blue is superimposed with the reconstructed surface. (e) The pose of the preoperative model as estimated by our approach using only stereo measurements. (f) The pose of the preoperative model as refined by our approach using contact measurements. (g) Left and right camera views with the preoperative model overlayed at the right pose.

IV. Results

The estimated registration conforms well with the true pose of the organ visually and shows a low surface registration error (see Fig. 1(g)). The registered model of the organ is overlaid in blue whereas the organ is shown as a point cloud. The filtering-based registration [21] used in Step 4 and the probabilistic sparse point registration [20] used in Step 6 have lower computation time compared to ICP as shown in Table I[1]. We only provide comparison with ICP in this work, as the results in [21] and [20] describe in detail the improved performance over state-of-the-art methods.

In some instances where the object consists of sufficient visual features for generating a detailed disparity map and reconstruction, the registration error decreases drastically after Step 2 (as shown in Fig. 3). We observe that when the registration estimate from Step 2 is inaccurate due to noisy measurements or specular reflection, the contact points help refine and obtain an accurate estimate. The obtained accuracy is well within the clinical requirements [6].

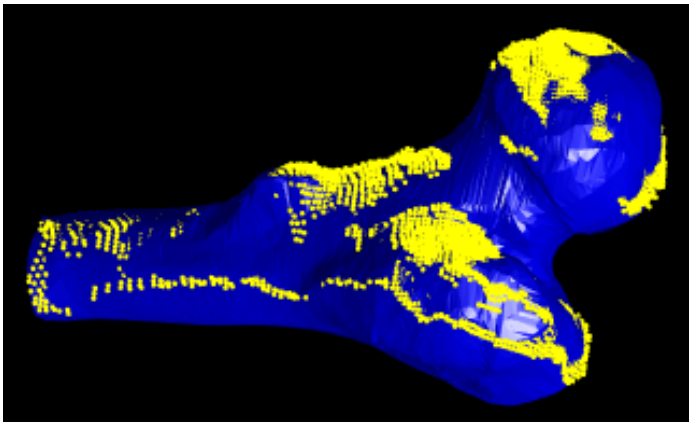

Fig. 3. Registered preoperative model of femur (shown in blue) overlaid on stereo point cloud (shown in yellow).

TABLE I

	RMS (mm)	Time (s)
ICP (Stereo only)	2.4	3.66
ICP (Stereo and Contact)	0.99	4.65
Our approach (only stereo)	2.8	0.40
Our approach(stereo and contact)	0.99	0.69

V. Discussions and Future Work

In this work, we have developed an approach that uses complementary information from stereo imaging and as few as 10 contact measurements to estimate the registration between intraoperative and preoperative information. The results show that our approach is robust, accurate and computationally faster than standard registration methods.

[1]The computational time taken is calculated for script written in MATLAB R2015a software from MathWorks, running on a ThinkPad T450s (20BX0011GE) laptop from Lenovo with 8 GB RAM and intel i7 processor.

Depending on the sensitivity of the contact sensing, local surface deformations may occur when probing. In the future we plan to compensate for this deformation using simultaneous force and position measurements as shown in [19]. While silicone phantoms serve as a platform to perform repeatable experiments, in the future we plan to demonstrate our approach on exvivo organs to simulate realistic surgical scenarios.

Future work includes using the registered preoperative model to perform tasks such as tumor detection with stiffness mapping [1], autonomous suturing and ablation [17], implementing virtual fixtures for guided telemanipulation [22] and needle steering for drug delivery [15].

Acknowledgments

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